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Analysis of the Educational Application User's Satisfaction Levels by Using the Integrated Entropy Weight-VIKOR Method

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ABSTRACT

A product review is an essential metric to understand the acceptability level of users. This rating process is often implemented to measure the quality and excellence of a product. It also helps the decision-making processes of potential users regarding the implementation of applications, due to the observation of many options. Furthermore, a product review enables the comparison of applications before imminent subscription. In this case, potential users often analyze various rating levels and perform selection within the Google Play Store based on the experiences of other subscribers. The review is also found to benefit students and software developers, concerning the strengths and weaknesses of the applications. For developers, subsequent modifications of products are mostly supported by this rating process during development. From this context, users and developers need to incorporate Multi-Criteria Decision-Making (MCDM) models, to understand the best and worst applications. Therefore, this study aims to assess the important criteria expected by users of seven educational service applications, by using the integrated Entropy Weight-VIKOR method. In this report, the service applications were selected based on the highest number of users in the Google Play Store.All criterion's mass was also calculated through the entropy weight method. To rank the application through eight selected criteria, the VIKOR method was subsequently used. The results showed that the best educational service application qualities were Khan Academy and Udemy, with Socratic being the lowest. Some criteria such as download (Cr_1), video (Cr_2), cost (Cr_3), and teacher (Cr_8) were also suggested for improvement. From these results, the*v*-value did not affect the rankings of Khan Academy, Udemy, or Socratic, although it influenced the positions of other applications. This indicated that Khan Academy and Udemy had excellent customer satisfaction levels, regarding functionality and few specific complaints. However, Socratic had high complaints from individuals and low users satisfaction. Based on these results, a comparative analysis was carried out with the baseline study, for analytical validation. In this case, better outputs were observed for the present study than the baseline analysis, due to having three stable ranking positions.

Keywords: Educational application service; Entropy weight method; Information and communications technology skills; Technology education; VIKOR

1. INTRODUCTION

Several courses assisting the academic performance of students are provided by the educational service applications in the Google Play Store. These applications are mostly downloaded anywhere and anytime through internet-based mobile devices, which are the gateway to digital learning.[1] In this case, students commonly tend to collaborate with teachers and their peers irrespective of the course materials. From this context, some courses are accessed freely, with others being paid.[2] Most paid courses provide unlimited time and qualifying exams to access learning materials and earn certificates, compared to free lessons. Since many options are available, students are observed to often compare the applications through the reviews on the Google Play Store. This allows them to select and subscribe to suitable learning materials based on other users' experiences. Besides the observation as a text, the review process is also in the form of a numeric rating.[3] This leads to the influence of online reviews on decision-making, which is popular and widely recognised, with several previous studies proving its effects on the preference behaviour and intentions of users.[4-7] From this context, rating process also benefits the students and software developers, regarding the awareness of the strengths and weaknesses of the applications.

Genuine reviews are always based on users experiences and a high number of ratings, which often enhance the possibility of reading and understanding all reviews. In this case, students often read the overall numeric rating more comprehensively than the text review having more specific information about the applications. This leads to the crucial need to develop a review-analysing system, to

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generate a ranking order of the best applications through numerical and text ratings. Several previous studies[8-13] have also reportedly analyseda customer's product review, concerning its implementation as a decision-making system. For the extension of this knowledge, the review of several well-known educational applications needs to be analysed.

According to Zhao, *et al.,*[14], the Entropy Weight Method (EWM) was applied to improve the objectivity of comprehensive evaluation. This method is practically and presently used in the decision-making model within various areas.[15] For instance, Delgado and Romero[16] measured the probability of mining environmental conflicts, by integrating EWM and clustering in Northern Peru. Li[17] also used the method to assess the ecological-geological environment, by comparing the proximity of each index TOPSIS model. From these descriptions, both reports applied EWM to the evaluation matrix. Meanwhile, Xu, *et al.*[18] used AHP to determine the value of the entropy weight method, toward developing information about the regional environment. Regarding these environmental science analyses, the revised entropy weight was then added to the AHP hierarchy model. In educational science, Yorulmaz & Can[19] also analysed the most important subjective and objective criteria, to improve the usability of MOODLE Learning Management System through EWM.

To assist people in making decisions based on preferences, a Multi-Criteria Decision-Making (MCDM) model is highly recommended for implementation.[20] TOPSIS, ÉLimination et Choix Traduisant la REalité (ELECTRE), VIKOR, and Analytic Hierarchy Process (AHP) are also some popular approaches of MCDM. From this description, VIKOR is used to investigate and consider ranking processes for the possibilities[21] meeting specific conditions.[15] To assess the quality of mobile apps,[22-23] VIKOR has reportedly been implemented by several reports, such as Dina,[23] *et al.* In this analysis, the decision matrix was modified by counting TF-IDF, to improve ranking output. This indicates that VIKOR is an MCDM method ranking and selecting possibilities from a list criterion. It also helps to determine solutions based on stated criteria. Moreover, the benefits of using the approach emphasise the dependence on personal judgments, as well as the implementation of valid statistics and data.

According to these benefits, the EWM and VIKOR methods are combined as evaluation options for educational service applications. This is because the EWM is able to objectively determine the weight of each index, with the VIKOR method effectively handling the fuzziness and uncertainty of assessment and decision-making processes.Therefore, this study aims to conduct the following objectives:

(a) Ranking and comparing the quality of educational service applications,
(b) Determining the satisfaction levels of users with educational application services, by using the EWM-VIKOR model, and
(c) Measuring the stability of the methods by providing a quantitative indicator.

The methodological stages used were data collection and pre-processing, users satisfaction evaluation with EWM-VIKOR, and system stability assessment through sensitivity analysis. Besides this, seven of the most popular available educational service applications were also emphasised. Based on the methodological stages implemented, the reviews from each application were initially obtained and stored in a database. This was accompanied by the preprocessing of the raw data, through Natural Language Processing. To assess users satisfaction estimation, the scores were then calculated by using EWM-VIKOR. Subsequently, a sensitivity analysis was carried out for the understanding of the system's stability.

2. METHODOLOGY

Figure 1 shows the proposed model, where the entropy weight-VIKOR methods were integrated into a framework. These data were obtained from the Google Play Store, with the interface of products' reviews shown in Figure 2. In this experiment, the data obtained were initially analysed through a pre-processing stage, for adequate analytical preparation. From this process, the keywords were then extracted through a text mining process. Further more, a decision matrix was constructed .

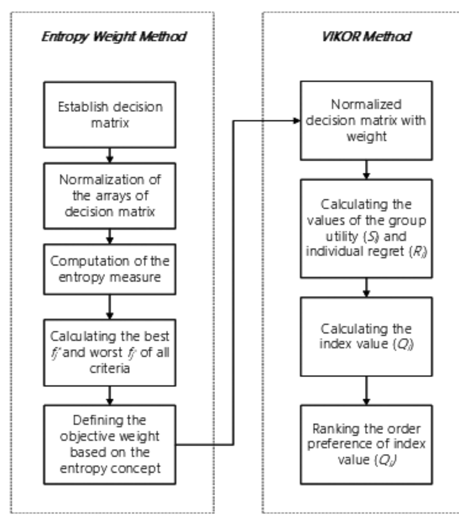

Figure 1. Proposed method.

2.1 Data Collection

Data were obtained through feature similarities, where the satisfaction levels of users were tested and contrasted by using the common elements gleaned from the review information. In this case, the Google Play store was scoured for the evaluations of various online education platforms, namely Coursera, edX, Khan Academy, LinkedIn Learning, Quipper, Socratic, and Udemy. Subsequently, 200 reviews were obtained from each application, leading to a total estimation of 1400 information from 2019 to 2021. Table 1 shows the sampling review from each application.

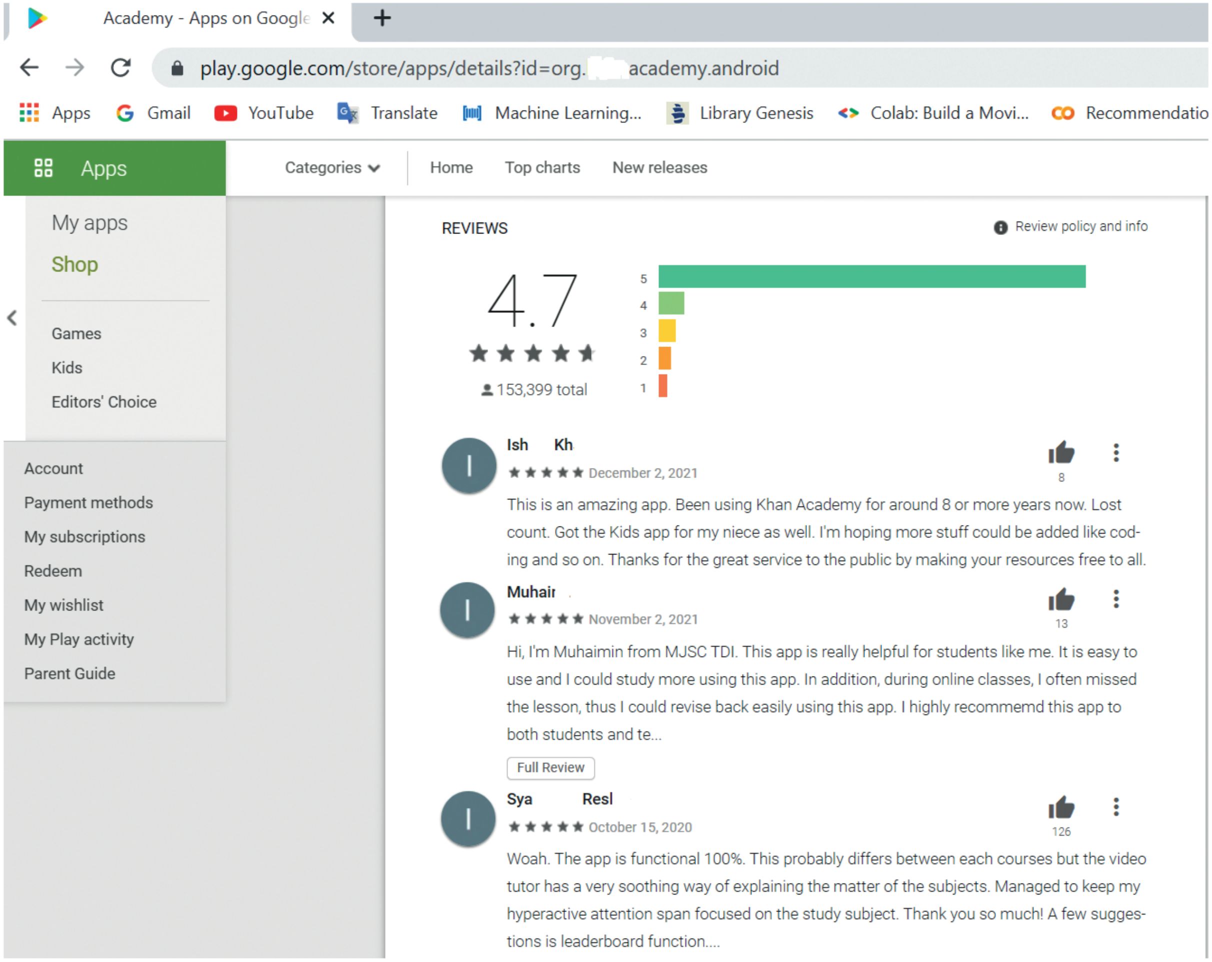

Figure 2. Product's review.

Table 1. Sampling review from each application

Application	Review	Rate
Coursera	"It's good.... But in the quizzes, the option was not visible. Only a few words are visible. We are unable to find the correct answer."	4
edX	"Great application I can learn many things freely and improve my English because they provide English subtitles under the video, thank you"	5
Khan Academy	"I have tried the website version. It is good but, the application is even.....BETTER. To all the people that workin Khan Academy "keep up the spirit and be unyielding to teach kids and teens like me."	5
LinkedIn Learning	"Many courses and useful information are enabled to learn and obtain certifications, personally, I think the opportunities are uncountable and all courses are certified by professional instructors, it was the best idea in virtual learning."	5
Quipper	"Hello, I just want to ask about my quipper account. My money in quipper went to zero after I linked my google account there. I just want to know how it happened. I hope that I'll get a response. Thank you!"	3
Socratic	"Not very helpful.If it's like 10×10 it can solve it, but it didn't help me find the area or length on the problem of the equation I was doing."	2
Udemy	"Not showing all sessions within a course. It just keeps loading, I cannot move forward upon finishing up session 17 or something, the entire course contains over 200 sessions. Where are the rest of them? Now I have to login through the browser to continue to watch the rest of all other sessions"	1

Table 2. Criteria and description

Criteria	Description
Download *(Cr_1)*	Ease to download
Video *(Cr_2)*	Tutorial video;s quality
Cost *(Cr_3)*	Learning fees
Assignment *(Cr_4)*	Practice material
Content *(Cr_5)*	Completeness of resources material
Course *(Cr_6)*	Several classes or talks provided on a specific topic or subject
Exam *(Cr_7)*	Aseries of official examinations or quizzes at the end of the course
Teacher *(Cr_8)*	Instructor of the course

2.2 Text Pre-processing and Text Mining

Text pre-processing is one of the critical phases implemented before the application of various methods. This phase includes cleaning stop words, punctuations, numbers, and other terms without any context weightage. It is also divided into five steps, namely, Tokenisation, Stop word filtering, Stemming, and Case transformation. Firstly, tokenisation is the splitting of strings into words and the deletion of non-letter characters, such as commas, spaces, full stops, etc. Secondly, stop-word filtering is the removal ofthe words having no information or pattern, such as question texts, conjunction, etc. Thirdly, stemming is responsible for reducing words into its stem and eradicating various text parts, including suffixes. Fourthly, case transformation is the normalisation of text through the conversion of uppercase into lowercase.

Text pre-processing is also the generation of a bag of words, which are classified into their Part-of-Speech (POS) tagging by using Stanford POS tagger[24]. This tagging process classifies each term into adjective, adverb, noun, numeral, and verb phrase. In this case, only noun phrases were used in the analysis, leading to the removal of other expressions from the bag of words. Moreover, a nounphrase was selected for classification as criteria[25] in the VIKOR method. From the analysis, the bag of words was then converted into a vector space model, accompanied by the provision of the numeric values very helpful in feature selection. The value of each term was also obtained by calculating the occurrence of noun phrases, which appear in the review. Regarding this description, the vector space model and its value were then categorised into eight criteria, as shown in Table 2. The functionality, reliability, and usability of the application were also considered in these criteria[26].

2.3 Entropy Weight Method (EWM)

The EWM is popular for its objectivity and impact on evaluation outputs, leading to wide implementation in the decision-making area. To obtain more information, EWM assessed the entropy value by calculating the degree of difference. This indicated that a smaller entropy value led to a low dispersion degree and vice versa.[27] Since the method was dependent on the information quantity to establish the weight of the index, a greater degree of dispersion then caused the acquisition of higher data values.[28] According to[29,30], the following steps were implemented to apply EWM,

Step 1: Construction of the decision matrix from keyword vectors

$$X = \begin{array}{c} \\ Alternative\ 1 \\ \dots \\ Alternative\ m \end{array} \begin{bmatrix} Criteria\ 1 & Criteria\ 2 & Criteria\ 3 \\ a_{11} & a_{12} & a_{1n} \\ a_{m1} & a_{m2} & a_{mn} \end{bmatrix} \tag{1}$$

Step 2: Normalisation of the deci sion matrix arrays, to obtain the project outcomes $p_{ij} p_{ij}$

$$p_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}} \tag{2}$$

Step 3: Computation of the entropy by using the following equation:

$$E_{ij} = -k \sum_{i=1}^{m} p_{ij} \ln p_{ij} \tag{3}$$

which $k = 1/lnk = 1/ln$(m).

Step 4: Definition of the objective weight

$$w_j = \frac{1-E_j}{\sum_{j=1}^{n} 1-E_j} \tag{4}$$

2.4 Measuring the Contentment of Users by Implementing Visekriterijumska optimizacija I Kompromisno resenje (VIKOR)

VIKOR is used to determine ranking from multiple criteria and is dependent on the closeness of the ideal solution, to obtain the preferred positions of several alternatives.[31-32] The following are the steps conducted by VIKOR, to rate various options,

Step 1: Construct the decision matrix

The multiplication of the attribute's occurrence and polarity value is used to generate keyword vectors, which are subsequently implemented to construct a decision matrix, as shown in Eq. (5).

$$X = \begin{array}{c} W_1 \\ W_i \\ W_m \end{array} \begin{bmatrix} C_{11} & C_{1j} & C \\ C_{i1} & C_{ij} & C \\ C_{m1} & C_{mj} & C \end{bmatrix} \tag{5}$$

Where, the *i*-th and *j*-th options symbolize W_i, and C_{ij}, respectively.

Step 2: Normalisation

In step 1, the attribute occurrence (x) from each criterion was normalised to a value between 0 and 1. Equation (6) shows the stated normalisation and the weighting technique used to determine the weight of each criterion (w_k). This was subsequently derivedthrough Equation (7), where $n_k(d)$ = the occurrence values of the k-th criterion.

$$x^{*} = \frac{x - \min(x}{\max(x) - \min} \tag{6}$$

$$w_k = \frac{n_k(d}{\sum_{k=1}^{m} n} \tag{7}$$

Step 3: Calculation of the best and the worst values Equation (8) was used to gain the positive (f_j^*) and negative (f_j) values

$$f_j^* = \max_i f_{i,j} \qquad and \qquad f_j^- = \min_i f_{i,j} \tag{8}$$

Step 4: Estimation of new weighted decision matrix Equation (9) was used to assign the weight (w_j) for a new decision matrix

$$\frac{w_j(f_j^* - f_{ij})}{f_j^* - f_{ij}^-}\frac{w_j(f_j^* - f_{ij})}{f_j^* - f_{ij}^-} \tag{9}$$

Step 5: Calculation of the individual regret (R_i) and group utility (S_i) values

The S_i, and R_i were counted by using Equations (10) and (11), respectively, where w_j = the weight of the criterion.

$$S_i = \sum_{i=1}^{n} \frac{w_j(f_j^* - f_{ij})}{f_j^* - f_{ij}^-} \tag{10}$$

$$R_i = \max\left[\frac{w_j(f_j^* - f_{ij})}{f_j^* - f_{ij}^-}\right] \tag{11}$$

Step 6: Estimation of the index value (Q_i)

The index value, Q_i, is calculated through the application of Equation (12), where S^* and S^- = the highest and lowest values,R^* and R^- = the maximum and minimum values of R_i, and v = the index weight value.

$$Q_i = v\left[\frac{S_i - S^*}{S^- - S^*}\right] + (1 - v)\left[\frac{R_i - R^*}{R^- - R^*}\right] \tag{12}$$

Step 7: Rank the preference

The result obtained was considered a lower quality when the index value (Q_i) was greater, and vice versa.

2.5 Sensitivity Analysis

Sensitivity analysis[33] is used for analysing the impact of uncertainty in a system's output when the inputs are unknown. To observe the influence of uncertainties, the inputs of the system are mostly adjusted gradually, with their corresponding effect on the outputs being analysed. The analysis is also used to determine small preference changes when the value of the parameter is changed[34]

3. RESULTS1 AND DISCUSSION

Based on the results, the scores calculated for each of the criteria (Cr_n) are presented in Table 3. This showed that the number of term present within each criterion is shown in the last row. Table 4 also presents the normalisation output, with the entropy weight technique used to determine the criteria mass employed in the VIKOR method.

Table 6 shows the positive (f_j^*) and negative (f_j^-) ideal solutions, which are the outputs with the highest and lowest values, respectively. Moreover, the revised decision matrix is illustrated in Table 7, which was developed by multiplying the normalised values by weight. From these results, the position of each application in the overall ranking was determined by its index value, Q_i, in Equation (12). In this case, the lowest value implied that people were most satisfied with various aspects. The utility (S_i) and regret (R_i) measures were also counted by Equations (10) and (11), with Download (Cr_1), Video (Cr_2), Cost (Cr_3), and Teacher (Cr_8) being the specific criteria needing improvement.

In Table 8, a sensitivity analysis was carried out to determine the seven educational applications with the highest and lowest index values. In this case, the data were examined for their degree of sensitivity to eight distinct influential factors. The results obtained were also examined for possible bias and variance, due to the weightings in these analyses. Therefore, the acquired v-values ranged from 0 to 1.

Figure 3 shows thatthe ranking positions of the best applications and the worst alternatives remain unaltered for all v-values.This proved that the v-value did not affect the rankings of Khan Academy, Udemy, or Socratic. In this case, Khan Academy and Socratic ranked first and last for the highest collective usefulness and least individual regret, respectively.Since the v-value was increased, the rank of LinkedIn Learning, Quipper, and EdX dropped simultaneously. Based on these results, the minimisation of individual regrets should be emphasised, to achieve better customer satisfaction levels. Meanwhile, the rank of Coursera increased to a higher position when the v-value was elevated. This confirmed that the maximum group utility value was directly related to the score assigned by Coursera.

Since Dina[23], *et al.* used VIKOR as one of the MCDM techniques during the assessment of user satisfaction, it was then implemented as the comparative baseline against this present analysis. In addition, the EWM was presently assigned before implementing the VIKOR technique, to

Table 3. Calculated scores

	Cr_1	Cr_2	Cr_3	Cr_4	Cr_5	Cr_6	Cr_7	Cr_8
Coursera	182	222	37	48	24	408	88	154
Edx	0	80	0	0	8	332	0	0
Khan Academy	203	638	218	124	160	1253	267	310
Linkedin Learning	30	53	0	499	802	0	36	0
Quipper	69	36	3	52	35	269	65	103
Socratic	0	0	0	263	104	265	224	0
Udemy	0	225	147	0	120	803	0	16
Term presence	53	216	38	47	175	487	64	51

Table 4. Normalised scores

	Cr_1	Cr_2	Cr_3	Cr_4	Cr_5	Cr_6	Cr_7	Cr_8
Coursera	0.37	0.17	0.09	0.04	0.01	0.12	0.12	0.26
Edx	0.00	0.06	0.00	0.00	0.00	0.10	0.00	0.00
Khan Academy	0.41	0.50	0.53	0.12	0.12	0.37	0.39	0.53
Linkedin Learning	0.06	0.04	0.00	0.50	0.64	0.00	0.05	0.00
Quipper	0.14	0.02	0.00	0.05	0.02	0.08	0.09	0.17
Socratic	0.00	0.00	0.00	0.26	0.08	0.08	0.32	0.00
Udemy	0.00	0.17	0.36	0.00	0.09	0.24	0.00	0.02

Table 5. Computation of the entropy measure

	Cr_1	Cr_2	Cr_3	Cr_4	Cr_5	Cr_6	Cr_7	Cr_8
Coursera	-0.38	-0.10	-0.03	-0.01	-0.01	-0.05	-0.06	-0.19
Edx	0.00	-0.02	0.00	0.00	-0.01	-0.04	0.00	0.00
Khan Academy	-0.48	-0.75	-0.86	-0.06	-0.06	-0.38	-0.4	-0.84
Linkedin Learning	-0.02	-0.01	0.00	-0.74	-1.43	0.00	-0.01	0.00
Quipper	-0.07	-0.01	-0.01	-0.01	-0.01	-0.03	-0.04	-0.10
Socratic	0.00	0.00	0.00	-0.20	-0.03	-0.03	-0.29	0.00
Udemy	0.00	-0.10	-0.35	0.00	-0.04	-0.17	0.00	-0.00
Sum	-0.96	-1.00	-1.26	-1.04	-1.58	-0.72	-0.83	-1.15
E_j	0.53	0.56	0.70	0.58	0.88	0.40	0.468	0.642
$1\text{-}E_j$	0.46	0.44	0.29	0.42	0.11	0.59	0.532	0.358
W_j	0.14	0.13	0.09	0.13	0.03	0.18	0.165	0.111

Table 6. Positive ideal solution

	Cr_1	Cr_2	Cr_3	Cr_4	Cr_5	Cr_6	Cr_7	Cr_8
f_j^*	0.419	0.509	0.538	0.506	0.640	0.376	0.393	0.532
f_j^-	0.000	0.000	0.000	0.000	0.006	0.000	0.000	0.000

obtain objective weight without the intervention of the user's choice from the review data.

In this study, the outputs obtained were compared to those of the baseline, where a similar diagram was comparatively analysed with the sensitivity analysis in Figure 3. Based on the results, this present report was more stable than the baseline. From the model stability (Figure 3), the ranking positions of the best two applications and the worst alternatives remain unaltered, indicating that the *v*-value did not influence the positions of Khan Academy, Udemy, or Socratic. However, only two stable positions were observed for the baseline study. This proved that EWM-VIKOR was used in the decision-making processes within the case study.

Based on the practical implication, the following statements were emphasised. Firstly, the EWM-VIKOR method needs to be used to support the decision-making processes in defining and solving choices, as well as the ranking and sorting of the selection of the educational service application. Secondly, the method should allow the comparison of several criteria, to contribute to the development of a learning process influential on the decision-making stages.However, the following limitations were observed. Firstly, the implemented applications were only seven applications, indicating that more software needs to be futuristically adopted to increase robustness. Secondly, the number of review data was limited to only 1400, proving that more information should be obtained

Table 7. Normalised decision matrix with weight

Cr_1	Cr_2	Cr_3	Cr_4	Cr_5	Cr_6	Cr_7	Cr_8
0.015	0.089	0.076	0.118	0.035	0.125	0.111	0.056
0.144	0.119	0.091	0.130	0.036	0.137	0.165	0.111
0.000	0.000	0.000	0.098	0.029	0.000	0.000	0.000
0.123	0.125	0.091	0.000	0.000	0.186	0.143	0.111
0.095	0.129	0.090	0.117	0.035	0.146	0.125	0.074
0.144	0.137	0.091	0.062	0.032	0.147	0.027	0.111
0.144	0.088	0.030	0.130	0.031	0.067	0.165	0.106

Table 8. Q values

S_i	R_i	$Q_i(v=0, \ldots, 1)$										
		0	*0.1*	*0.2*	*0.3*	*0.4*	*0.5*	*0.6*	*0.7*	*0.8*	*0.9*	*1*
0.625	0.125	0.928	0.897	0.866	0.835	0.804	0.773	0.741	0.710	0.679	0.648	0.617
0.934	0.165	1.765	1.689	1.612	1.536	1.459	1.383	1.306	1.230	1.153	1.077	1.000
0.127	0.098	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
0.779	0.186	1.808	1.708	1.608	1.508	1.408	1.308	1.208	1.108	1.008	0.908	0.808
0.810	0.146	1.393	1.338	1.284	1.229	1.175	1.120	1.065	1.011	0.956	0.902	0.847
0.749	0.147	1.324	1.268	1.213	1.158	1.103	1.047	0.992	0.937	0.882	0.826	0.771
0.761	0.165	1.551	1.474	1.398	1.321	1.245	1.168	1.091	1.015	0.938	0.862	0.785

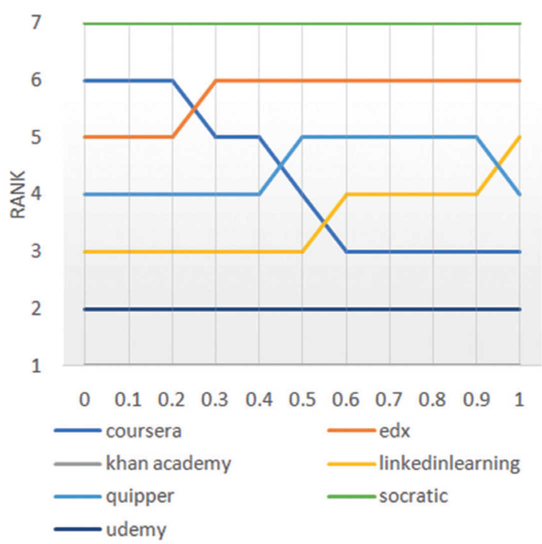

Figure 3. Sensitivity Analysis.

for high accuracy. Thirdly, the entropy weighted-VIKOR technique was included in the adopted MCDM strategy. This stated that future reports need to perform a comparative analysis with different MCDM approaches, to back up the results obtained.

4. CONCLUSION

Based on the results, the qualities found in seven different educational applications were evaluated through the entropy weight-VIKOR method. This indicated that the expert scoring technique was more objective by employing the entropy weight method. Regarding many different criteria, the VIKOR method was used to rank the best and worst alternatives, where Khan Academy and Socratic had the highest and lowest satisfaction levels, respectively. Moreover, the maximum group utility and individual regret influenced the satisfaction levels of the users. By using an eight-factor sensitivity test, the rankings of the top two applications and worst alternatives remained unchanged. This was because the v-value did not influence the rankings of Khan Academy, Udemy, or Socratic. For subsequent validation, future reports should be performed by using another MCDM approach. To improve the criterion directory, the amount of data used needs to be increased. The implemented criteria in future analyses should also be broader than the eight standards used in this study.

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